A memetic algorithm for a relocation-routing problem in green production of gas considering uncertainties

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ABSTRACT

This study introduces a relocation-routing problem with a fuzzy amount of sewage and stochastic travel time in natural gas production. In this study, a set of sewage treatment plants (STPs) and a certain number of gas-gathering stations (GGGs) are distributed on the field. With the increasing amount of production, however, the current STPs cannot satisfy the production level. Policymakers propose several location candidates to build new STPs and aim to minimize the total cost of running the newly built STPs and the original STPs. The practical attributes of the sewage return logistics, capacity of vehicles and STPs, uncertain amount of sewage, stochastic travel times, and other constraints are taken into account. The new problem proposed in this study is defined as Relocation-Routing Problem with Fuzzy Sewage and Stochastic Travel Time (RLRPFSSTT), which has never been investigated before. To minimize the total cost, including the construction cost of newly opened STPs and transportation cost between STPs and GGGs, this paper designs a memetic algorithm to optimize location and routing problems simultaneously. Benchmark-based experimental data is designed, and the computational results demonstrate the effectiveness of the proposed memetic algorithm. Sensitivity analysis and comparisons are also carried out to validate the advantage of considering uncertainties. The proposed model and algorithm are meant to further supplement and extend the location and routing models, as well as have great significance for the decision-makers of industrial logistics in oil fields and coal mines.

1. Introduction

During the past decade, the logistics industry has witnessed extraordinary growth. Stepien et al. [1] disclosed that the transportation cost had accounted for a significant part of the logistics cost. Notably, this value in developing countries, such as China, was about 70% to 90% [2]. Therefore, the optimization of material transportation and distribution is of great significance for reducing logistics costs, as well as improving the operational efficiency of enterprises.

A local gas enterprise, abbreviated LGE (Considering privacy, we are not convenient to disclose the name of the enterprise here. This article uses LGE to indicate the name of the company), has many gas-gathering stations (GGGs) and sewage treatment plants (STPs). Usually, LGE is located in a remote area with complex geomorphology. In each GGG, sewage, including condensate and methanol, is frequently generated daily during the pipe network operation in the production. These sewage need to be transported to the STPs for purification and separation, thereby refining useful substances such as condensate and methanol. With the expansion of each GGG’s production scale, the throughput of the original purification plant cannot meet the production requirements. To deal with this situation, policymakers proposed several candidate locations for building new STPs and aimed to minimize the total cost of running the newly built STPs and original STP.

The STP relocation problem is an extended version of facility location problem (FLP), which is a medium-term or a long-term decision-making of enterprises depending on the problems and has vital strategic significance for the development of enterprise’s logistics. However, rerouting problem is a variation of VRP, which is a short-term or a medium-term decision-making process for enterprises and has a crucial tactical reference value for logistics distribution for enterprises. From the logistics in practice, FLP and the VRP have much intrinsic relevance...
in the decision-making process: both should generally consider the distribution of materials distribution centers and gas-gathering stations (GGSs).

The procedures of identifying the final location of the STPs can be listed as follows: Firstly, the policy-makers need to provide a few candidate locations for constructing STPs by evaluating the relevant conditions, including land accessibility and environmental factors. Secondly, the specific opened facilities should be selected. The goal is to construct STPs with minimizing the total costs, including the construction cost of STPs, and transportation cost between STPs and GGSs by considering the uncertain capacity of STPs and uncertain transportation time between STPs and GGSs. From the practice of the GGS, observed that the amount of generated sewage (AGS) is not a deterministic value each day. Actually, the AGS has a great relationship with the daily temperature, humidity, air pressure, the actual amount of gas production and other complex factors. So, it is unpredictable even by some experienced workers. Additionally, the gas filed is located in mountainous maybe with complex terrain. In these areas, the travel time between each arc is non-deterministic due to the rugged road, changeable and inclement weather. So, it is of great significance to consider these uncertainties when modeling our problem [3,4]. It is of great importance to integrate the two issues simultaneously, which was defined as location routing problem (LRP) [5]. This paper studies the STP relocation problem and rerouting problem considering the uncertainties of amount of AGS and travel time, which has never been investigated before. Fig. 1a presents the current situation faced by a LGE and the proposed solution method. Fig. 1b gives a solution scenario after applying the sensitivity analysis is also performed to help the policy-makers make a reasonable decision.

(5) Benchmark based instances are introduced and the experimental results demonstrate the effectiveness and efficiency of the proposed memetic algorithm, as well as the advantage of considering uncertainties in the model.

The remainder of the paper is organized as follows. Section 2 analyzes the relevant literature. The mathematical formulation and memetic algorithm are presented in Sections 3 and 4, respectively. Computational experiments are given and analyzed in Section 5. Finally, the conclusions and future studies are presented in the Section 6.

2. Literature review

Considering that the studied problem is regarded as a further extension of the classical location-routing problem with considering the uncertainties. The literature review section is composed of four categories. First, the recent works on VRP and scheduling are discussed, then recent works about LRP are investigated. After that, the recent works on routing and scheduling problems with uncertainties are presented. Finally, we discuss the related work with the memetic algorithm, which is the main methodology in this study.

2.1. Vehicle routing and scheduling problem

Capacitated vehicle routing problem (CVRP), which could be regarded as a multi-traveling salesman problem with
programming method) tend to be powerless. The meta-heuristic algo-

mating, branch and bound method, cutting plane method, and dynamic

uration of FLP and VRP. When the size of clients and facilities are

taking into account the energy consumption criteria. In order to solve

et al. [8] investigated a blocking flow shop scheduling problem with

self in the specific application process and make the final solution close

Meta-heuristic algorithms obtain the solution through the global search

methods and can temporarily accept the poor solution that appears in the

search process. Meta-heuristic algorithms will improve the solution it-

self in the specific application process and make the final solution close
to the optimal solution as much as possible. Common meta-heuristic
algorithms have been applied to solve the classical VRP problem. These
meta-heuristics include Genetic Algorithm, Simulated Annealing
Algorithm, Tabu Search Algorithm implemented by Particle Swarm
Optimization, Ant Colony Algorithm etc. Additionally, nesting and
mixed algorithms are designed to improve the solution of the instances
further.

Han et al. [7] studied the job shop scheduling problem with taking
into account minimizing the economic cost and the energy consumption.
In this work, a multi-objective optimization is constructed, and to solve
the model, the authors designed a discrete evolutionary algorithm. Qin
et al. [8] investigated a blocking flow shop scheduling problem with
taking into account the energy consumption criteria. In order to solve
the model, a modified iterated greedy local search is proposed. Experi-
mental results for 140 benchmark instances have been reported, and the
comparison performed with the state-of-the-art highlight the efficiency of
the improved algorithm.

2.2. Location routing problem

LRP is also an NP-hard problem, which can be viewed as the com-
bination of FLP and VRP. When the size of clients and facilities are
slightly larger, traditional exact algorithms (such as linear program-
mimg, branch and bound method, cutting plane method, and dynamic
programming method) tend to be powerless. The meta-heuristic algo-
rithms are the most commonly used approach to obtain a satisfactory
solution. In an attempt to find a better solution or lower bound for LRP,
many works [9–11] developed heuristics based on the attributes of the
problem. Especially, Prins et al. [10] proposed a two-phase approach to
solve the LRP problem. In the first phase, the routes and their customers
are grouped into super-clients, which poses a problem of location of the
facilities, which is then resolved by Lagrangian relaxation of the

considering the capacitated constraints, was first proposed and defined
by Dantzig and Ramser [6] and it is one of the most basic and represen-
tative models in the family of VRPs. The algorithms for solving VRP
are divide into two classes: namely exact algorithms and heuristic al-
gorithms. Exact algorithms mainly include Dynamic Programming,
Branch and Bound, and Lagrangian relaxation, column generation etc.

 Meta-heuristic algorithms obtain the solution through the global search

method and can temporarily accept the poor solution that appears in the

search process. Meta-heuristic algorithms will improve the solution it-

self in the specific application process and make the final solution close
to the optimal solution as much as possible. Common meta-heuristic
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facilities, which is then resolved by Lagrangian relaxation of the

assignment constraints. In the second phase, routes from the resulting
multi-destination VRP are enhanced using a granular tabular search
heuristic.

2.3. Routing and scheduling problem with uncertainties

In the real practice of routing and scheduling problem, many factors
such as customer’s demand, travel time, etc. are not always determin-
istic. If we ignore these uncertainties when modeling the problem, the
optimal solution obtained may be not reasonable enough when apply
into practice. Fuzzy theory and stochastic probability provide effect-
tive tool for describing uncertainties. In the past 10 years, many researchers
have introduced fuzzy theory into FLP [12], LRP [13], and Vehicle
Routing Problem [14]. Afars et al. [15] proposed a multi-objective
optimization model to solve the job shop scheduling problem with
taking into account the uncertain times. More applications, in recent
years, are summarized in Table 1. However, compared with the classical
LRP and its extension, the relocation-routing problem is less

2.4. Memetic algorithms

On the basis of the genetic algorithm that simulates the biological
evolution process, Moscato and Cotta [26] proposed a memetic algo-
rithm (MA) that simulates the cultural evolution process. MA is regard-
as one of the most powerful population-based evolutionary algorithms,
and a comprehensive survey of MA was conducted by Chen et al. [27],
Neri and Cotta [28], Krasnogor and Smith [29].

Some early results about MA for routing problems are reported by
Prins and Bouchenoua [30]. Labadi et al. [31] made the earliest attempt
to design MA for solving the vehicle routing problem and time window.
The main structure of MA is composed of the basic genetic algorithm and
the local search operators, which provides a learning strategy for an
individual in the genetic algorithm. Experimental results on the 56
classical benchmark instances [32] demonstrated that the designed MA
is efficient. Ngueveu et al. [33] proposed a MA for solving the classical
cumulative capacitated vehicle routing problem (CCVRP), which
considered minimizing the sum of the arrival time at customers. This
work presented the lower bound and upper bound of the CCVRP.
Specifically, the upper bound was obtained by the proposed MA. Nagata
et al. [34] investigated the solving approach of VRPTW by introducing a
new MA, which is composed of a new operator: existing edge assembly
crossover. Additionally, they proposed a novel penalty-based function
to eliminate capacity and time windows violations. The intensive experi-
mental results demonstrated that their algorithm could reach remark-
able results compared with the published results. Mendoza et al. [35]
proposed the results for solving the vehicle routing problem with sto-

castic demand.

Wang et al. [36] studied the multi-objective periodic VRPTW by
proposing a MA. Meanwhile, Wang and Lu [37] investigated a MA for
solving the competition for a green CVRP. García-Ródenas et al. [38]
integrated MA and gravitational search algorithm to train the feedfor-
ward neural networks, and simulation results showed that the proposed
framework works well.

Many researchers regarded MAs as hybrid genetic algorithms or

genetic local search. In fact, MAs provide a framework or a concept.
Under this framework, different search strategies are used. Dengiz et al.
[39] investigated the communication network topologies optimization
problem by designing a hybrid genetic algorithm and local search with
specialized encoding and initialization. Asadzadeh [40] implemented a
local search genetic algorithm to solve the job shop scheduling problem
with agents.

Compared with the analysis above, we conclude the following two

points.

Table 1

Recent research related to fuzzy variables and optimization.

<table>
<thead>
<tr>
<th>Authors</th>
<th>Studied problem</th>
<th>Solving approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cao and Lai [16]</td>
<td>Open vehicle routing problem</td>
<td>Differential Evolution</td>
</tr>
<tr>
<td>Zarandi et al. [17]</td>
<td>Capacitated Location-routing problem</td>
<td>Simulated Annealing</td>
</tr>
<tr>
<td>Sadeghi et al. [18]</td>
<td>Hybrid vendor-managed inventory and transportation problem</td>
<td>PSO</td>
</tr>
<tr>
<td>Sarkar and Mahapatra [19]</td>
<td>Fuzzy inventory model</td>
<td>Heuristic algorithm</td>
</tr>
<tr>
<td>Berrichi et al. [20]</td>
<td>Joint Integration of Production Planning</td>
<td>Multi-objective GA</td>
</tr>
<tr>
<td>Bahri et al. [21]</td>
<td>Multi-objective VRP</td>
<td>Scalable algorithms</td>
</tr>
<tr>
<td>Sun et al. [22]</td>
<td>Flexible job shop scheduling</td>
<td>hybrid cooperative co-evolution algorithm</td>
</tr>
</tbody>
</table>
| Li et al. [25]           | Flexible job shop scheduling                  | Self-adaptive multi-objective evolu-

tionary algorithm                      |
Notations in the mathematical model.

<table>
<thead>
<tr>
<th>Notations</th>
<th>Descriptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>OS</td>
<td>set of the original existing STP.</td>
</tr>
<tr>
<td>N</td>
<td>set of GGSs.</td>
</tr>
<tr>
<td>CS</td>
<td>the set of candidates of STPs.</td>
</tr>
<tr>
<td>F = OS ∪ CS</td>
<td>set of STP.</td>
</tr>
<tr>
<td>N_0 = F ∩ N</td>
<td>set of all the vertices, including STPs and GGSs;</td>
</tr>
<tr>
<td>K</td>
<td>set of the vehicles.</td>
</tr>
<tr>
<td>v_0</td>
<td>average driving speed during GGSs i and j</td>
</tr>
<tr>
<td>w</td>
<td>the price for a unit distance.</td>
</tr>
<tr>
<td>C = (i,j) : i,j ∈ N</td>
<td>transportation cost matrix, and each element c_{ij} = w ∗ \tilde{c}_{ij}v_0</td>
</tr>
<tr>
<td>N</td>
<td>set of STP.</td>
</tr>
<tr>
<td>CF_i</td>
<td>fixed cost of STP i</td>
</tr>
<tr>
<td>CV_k</td>
<td>fixed cost of vehicle k</td>
</tr>
<tr>
<td>SC_i</td>
<td>capacity of STP i</td>
</tr>
<tr>
<td>VC_k</td>
<td>capacity of vehicle k;</td>
</tr>
<tr>
<td>d_i</td>
<td>fuzzy AGS of GGS i</td>
</tr>
<tr>
<td>d_i0</td>
<td>fixed cost of vehicle</td>
</tr>
<tr>
<td>T_i</td>
<td>loading time for the sewage at GGS i</td>
</tr>
<tr>
<td>DPI</td>
<td>dispatcher preference index</td>
</tr>
<tr>
<td>API</td>
<td>assignment preference index</td>
</tr>
<tr>
<td>\tilde{t}_{ik}</td>
<td>travel time on arc (i,j) in route k in the scenario ξ</td>
</tr>
<tr>
<td>AC</td>
<td>additional cost generated by the failure route in an uncertain environment</td>
</tr>
<tr>
<td>PC</td>
<td>planned cost for a specific solution in an uncertain environment</td>
</tr>
<tr>
<td>TC</td>
<td>total cost for a given solution in an uncertain environment</td>
</tr>
</tbody>
</table>

(1) Despite the abundant studies about LRP, the current works are aimed at helping companies plan a completely new logistics layout. In developing countries, such as China, many companies are facing business expansion. This means that the most primitive logistics layout cannot meet the growing development needs. Therefore, it is necessary to optimize further and add new logistics facilities on the basis of the original logistics facility layout to keep the entire logistics system in an optimal state. Therefore, this research is an essential reference value for making up for the existing deficiencies and providing logistics decision-making for developing enterprises.

(2) Despite the abundant investigations considering uncertainties in their models, few of them considers the fuzzy variables and stochastic variables simultaneously. This work derives the formulations of AGS under fuzzy chance constrained programming, and designs a reasonable chromosome structure. Then the complex constraints are incorporated into the MA to obtain an approximate optimal solution of the problem.

To sum up, our work formulates a relocation-routing problem with considering fuzzy AGS and stochastic travel time, then MA based heuristic is developed to solve this issue. Finally, experimental results show the advantage of viewing the uncertainties when modeling the problem.

3. Problem formulation

This section gives details about the mathematical formulation of the studied problem. The description of fuzzy AGS is given in Section 3.1, then the assumption and the fuzzy chance programming are presented in Section 3.2. Finally, the important constraints related to fuzzy demand and stochastic travel time are clarified in Sections 3.3 and 3.4, respectively.

3.1. Fuzzy AGS

In this section, the theory of fuzzy credibility [41] is employed to describe the uncertain variables of AGS. Let us consider the triangle fuzzy variable \( \tilde{d}_i = (d_{i1}, d_{i2}, d_{i3}) \) as the AGS of a given GGS i, the detailed introduction about \( \tilde{d}_i \) is shown in the supplementary material. Let \( r \) be a deterministic parameter. Let \( \text{Cr}(\cdot) \) be the credibility operator, we can derive the formulation (1) to calculate the chance that the event \( \tilde{d} \geq r \) happens [3,41].

\[
\text{Cr}(\tilde{d} \geq r) = \begin{cases} 
1, & \text{if } r \leq d_{i1}; \\
\frac{2d_{i2} - d_{i1} - r}{2(d_{i2} - d_{i1})}, & \text{if } d_{i1} \leq r \leq d_{i2}; \\
\frac{d_{i3} - r}{2(d_{i3} - d_{i2})}, & \text{if } d_{i2} \leq r \leq d_{i3}; \\
0, & \text{if } r \geq d_{i3}; 
\end{cases}
\] (1)

3.2. Assumptions and model

The assumptions of the model are itemized as follows.

- The vehicles are homogeneous, i.e., each vehicle has an identical maximum speed, loading capacity, and empty vehicle weight.
- Each vehicle starts from the STP.
- Each vehicle cannot be used more than once.
- The AGS of each GGS i is a triangle fuzzy variable which can be described as \( \tilde{d}_i = (d_{i1}, d_{i2}, d_{i3}) \).
- The transportation cost between ith GGS and jth GGS is \( c_{ij} \).
- Each driver carries out one route in the process of loading sewage; in case that remaining capacity is not sufficient for the next GGS, he/she must return to the STP, and unload all the sewage of vehicle, then continues serving the remaining GGSs on the road (task list).

The studied problem in our work defined on a complete, weighted and undirected network \((N_0, E, C)\). The detailed notations are explained in Table 2.

Decision variables are described as follows.

\[
x_{ik} = \begin{cases} 
1 \text{ if the } k \text{th vehicle travels from GGS } i \text{ to GGS } j, \forall i, j \in N_0; \\
0 \text{ otherwise. }
\end{cases}
\]

\[
y_n = \begin{cases} 
1 \text{ if the } n \text{th candidate is selected to build the STP, } \forall n \in F; \\
0 \text{ otherwise. }
\end{cases}
\]

\[
z_n = \begin{cases} 
1 \text{ if the } n \text{th GGS is assigned to STP } n, \forall n \in F, \forall n \in N; \\
0 \text{ otherwise. }
\end{cases}
\]

\[
\min z = \sum_{k \in K} \sum_{i \in N_0} \sum_{j \in N_0} c_{ij}x_{ik} + \sum_{a \in A} CF_a x_a + \sum_{a \in A} \sum_{i \in N} \sum_{k \in K} CV_k x_{ik} + AC
\]

subject to

\[
\sum_{k \in K} \sum_{i \in N_0} x_{ik} = 1, \forall i \in N
\]

\[
\text{Cr}(\sum_{j \in N} \sum_{k \in K} d_{ik} x_{ik} - VC_k \leq 0) \geq DPI, \forall k \in K
\]

\[
\sum_{j \in N_0} - \sum_{j \in N_0} x_{ik} = 0, \forall i \in N, k \in K;
\]

\[
\sum_{a \in A} \sum_{k \in K} x_{ik} \leq 1, \forall k \in K;
\]

\[
\sum_{i \in N_0} x_{ik} \leq |S| - 1, \forall i \in N, k \in K
\]

\[
\sum_{j \in N} x_{ij} + \sum_{a \in A, a \in N} x_{ij} \leq 1 + z_n, \forall i \in N, j \in N, k \in K;
\]

\[
\text{Cr}(\sum_{j \in N_0, j \in N_0} d_{ij} y_{ij} - SC_j y_{ij} \leq 0) \geq API, \forall i \in F.
\]

\[
P(\sum_{a \in A, a \in N} x_{ij} \leq B) \geq \alpha
\]
\[ y_i = 1; \forall i \in OS; \]  
\[ x_{ij} \in \{0, 1\}, \forall i \in N, j \in N, k \in K; \]  
\[ y_i \in \{0, 1\}, \forall i \in F; \]

The objective function (2) aims to minimize all the costs, including transportation cost, the fixed cost of the vehicles and STPs, as well as the additional cost of AC caused by failure route in the fuzzy environment. Here we should emphasize that the approach of calculating AC can be...
obtained by Algorithm 3, which will be described later. The constraints (3) ensure that each GGS belongs to one and only one route and that each GGS has only one predecessor in the circuit. Capacity constraints with fuzzy variables of vehicles and STP are satisfied by inequalities (4) and (9) respectively. The constraints (5) and (6) ensure the continuity of each route and the return to the original STP. Constraints (7) are the subtours elimination constraints. Constraints (8) specify that a client can be assigned to a repository only if a route linking them is open. Typically, (10) describes the constraints of stochastic travel time, which is adapted from Zhang et al. [42]. Finally, the constraints (11)–(13) state the binary nature of the decision variables.

As described above, constraints (4), (9), and (10) belong to the chance-constraints, which could not be applied to the solving approach directly. So, in the following two sections, we will transfer these constraints to the crisp equations [41].
input: a solution (sol) that composed the information of STPs and routes assignments.

initialization: m, n, k, segments; vehicleIndex=0; // the index of a vehicle
customerID=0; // the index of a customer

for i = 1:n do
  if(sizeOf(sol[i])!=0) // if the i th STP is not closed
    for j=1:sizeOf(sol[i]) do
      segments[2][vehicleIndex]←i;
      for h=1:sizeOf(sol[i].route) do
        segments[0][customerID]←vehicleIndex;
        segments[1][customerID]←sol[i].route[h];
        customerID++;
      end
      vehicleIndex++;
    end
  end
end

Output: segments.

Algorithm 1. Encoding process: from a solution to a chromosome.

Input: a chromosome composed by three segments, named segments[0], segments[1] and segments[2].
Initialization: paths=null; sol=null; vehicleSet=unique(segments[0]). // unique is a function to get the unique elements in the array

for i = 1:sizeOf(segments[1]) do
  for j=1:sizeOf(vehicleSet) do
    end
  if segments[0][segments[1][i]]==j then
    paths[j].add(segments[1][i]); // the node is added to the route with jth vehicle
  end
end

for i = 1:sizeOf(STPSet) do
  for j = 1:sizeOf(segments[2]) do
    if segments[2][j][i]==i then
      sol[i].add(paths[j]);
  end
end

Output: The solution.

Algorithm 2. Decoding process: from a chromosome to a solution.
3.3. Description of fuzzy chance constraints

In the deterministic model, it is straightforward to describe the capacity constraints: the total AGS of the whole route should not exceed the vehicle capacity. However, in the RLRPPFSSTT, the capacity constraints become more complex than the deterministic ones. Now, we have to consider the relationship between the fuzzy AGS and the capacity of the vehicles [43].

Indeed, in the planning stage, after serving the $j$th GGS, the remaining capacity (RC) also becomes a fuzzy variable named $\widetilde{RC}_j$, where

$$\widetilde{RC}_j = VC - \sum_{i=1}^{j} d_i = \left( VC - \sum_{i=1}^{j} d_{ij}, q - \sum_{i=1}^{j} d_i, VC - \sum_{i=1}^{j} d_i \right)$$

$$= (RC_{1j}, RC_{2j}, RC_{3j}).$$

In the deterministic model, if the remaining capacity of the vehicle is higher than the GGS’s AGS, this vehicle has the full chance to serve this GGS. However, when dealing with a fuzzy variable of AGS and remaining capacity, how can we decide whether the vehicle should continue visiting the $(j+1)$th GGS or go to the STP directly? Fuzzy credibility theory plays a crucial role to measure the relationship between the AGS of $(j+1)$th GGS and RC, which can be calculated by Eqs. (15) and (16).

$$Cr = Cr\{\widetilde{d}_{j+1} \leq \widetilde{RC}_j\} = Cr\{\{d_{j+1} - RC_{3j}, d_{j+1} - RC_{2j}, d_{j+1} - RC_{1j}\} \leq 0\}$$

$$Cr = Cr\{\widetilde{d}_{j+1} \leq \widetilde{RC}_j\} = \begin{cases} 
0, & d_{j+1} \geq RC_{3j} \\
\frac{RC_{3j} - d_{j+1}}{2(RC_{3j} - d_{j+1} + d_{j+1} - RC_{2j})}, & d_{j+1} \leq RC_{3j}, d_{j+1} \geq RC_{2j} \\
\frac{d_{j+1} - RC_{3j} - 2(d_{j+1} - RC_{2j})}{2(RC_{2j} - d_{j+1} + d_{j+1} - RC_{1j})}, & d_{j+1} \leq RC_{2j}, d_{j+1} \geq RC_{1j} \\
1, & d_{j+1} \leq RC_{1j} 
\end{cases}$$

(16)

According to our common sense, if RC is very high, and AGS of the next GGS is very low, the next GGS’s in this route tends to have more chance to get the service from the current vehicle. (16) shows the credibility $Cr \in [0, 1]$ to measure the event that RC is greater than AGS of next GGS on the current route. When $Cr = 0$, we declare that the vehicle does not have enough RC to serve the next GGS and it should terminate service at the current GGS and return to the STP to unload sewage. When $Cr = 1$, we can be completely sure that the vehicle should serve the next GGS due to enough RC. However, the difficulty is that, in most cases, $Cr$ is neither 0 nor 1, but $Cr \in (0, 1)$. Dispatchers must make a trade-off between risk and cost according to their working experience.

To describe the trade-off, let us introduce the dispatcher preference index DPI, where $DPI \in [0, 1]$. Note that $DPI$ expresses the dispatcher’s attitude toward risk. When the dispatcher is not a risk-averse, he/she will choose lower values of parameter DPI. This scenario indicates that the dispatcher prefers to make full use of the available vehicle capacity, although there is an increase in the number of situations, in which the vehicle arrives at the next GGS and is not able to carry out planned service due to small RC. On the other hand, when the dispatcher is a risk-averse, he will choose greater DPI, this may result in less complete utilization of vehicle capacity along the planned routes and less additional distance to cover due to failures [43].

Similarly, in constraints (9), if the STP’s RC for serving GGSs is high and the AGS at the next GGS is low, then the STP’s chance of loading the

---

Algorithm 3: Stochastic simulation.

1. for i from 1 to M do
2. for each GGS do
3. a ← 1, and u ← 0;
4. (1) randomly generate a real number $a$ in the interval between the left and right boundaries of the triangular fuzzy number representing AGS of the GGS, and compute its membership $u$;
5. (2) generate a random number $a$, if $a \leq u$, then "actual" AGS at the GGS is adopted as being equal to $x$.
6. (3) compare with if $a \leq u$, then "actual" AGS at the GGS is adopted as being equal to $x$.
7. end
8. end
9. end
10. Move along the route designed by memetic algorithm, calculate the TC, AC, PC due to route failures in terms of the
11. "actual" AGS.
12. Output: Compute AC which is the average value of additional distances obtained by M times simulation.
next GGS becomes greater. Here we rename a parameter Assignment Preference Index (API) to describe the risk. Here to guarantee the production, we order \( API = 1 \), which means the capacity of STP should be satisfied even if all the AGS are very high.

### 3.4. Transformation of fuzzy chance constraints

**Theorem 2.** Based on the crisp equivalent and Theorem 1 (please refer to Theorem 1 in the supplementary material), we transfer the fuzzy chance constraint to the crisp equivalent.

**Proof.** According the Theorem 1, let \( \xi_k = d_k, h_k(x) = y_k, y_k \in \text{Binary} \); so, we can get \( h_k^*(x) = h_k(x) \lor 0 = h_k(x) = y_k, h_k^*(x) = -h_k(x) \lor 0 = h_k(x) = 0 \), and finally we derive it to the Theorem 2.

**Theorem 3.** Based on the crisp equivalent and Theorem 1 (in the appendix), we can transfer the fuzzy chance constraint of capacity of STP to the crisp equivalent.

\[
\begin{align*}
&\left\{\begin{array}{ll}
(1 - 2 \times API) \sum_{i,j} d_{ij} z_{ij} + 2 \times API \sum_{i,j} d_{ij} y_{ij} - SC_{ij} \leq 0; & 1/2 \leq DPI \leq 1 \\
(2 - 2 \times API) \sum_{i,j} d_{ij} z_{ij} + (2 \times API - 1) \sum_{i,j} d_{ij} y_{ij} - SC_{ij} \leq 0; & 0 \leq API \leq 1/2
\end{array}\right.
\end{align*}
\]

**Proof.** The process of the proof is similar with Theorem 2.

The constrains (4) and (9) can be replaced by formulations (17) and (18).

### 3.5. Uncertainty of travel time

As mentioned before, the travel time on each arc is assumed to be independent and to satisfy to the normal distribution indicated by \( N(t_{ijk}, \sigma_{ijk}) \), where \( v_{ijk} \) is the average speed of the of vehicle \( k \) on arc \((i,j)\), and \( \sigma_{ijk} \) is the corresponding standard deviation [42].

The left part of the chance constraint (10) of the travel time for each vehicle \( k \) can be written as follows.

\[
\begin{align*}
&\left\{\begin{array}{ll}
(1 - 2 \times DPI) \sum_{i,j} d_{ij} x_{ijk} + 2 \times DPI \sum_{i,j} d_{ij} x_{ijk} - VC_{k} \leq 0; & 1/2 \leq DPI \leq 1 \\
(2 - 2 \times DPI) \sum_{i,j} d_{ij} x_{ijk} + (2 \times DPI - 1) \sum_{i,j} d_{ij} x_{ijk} - VC_{k} \leq 0; & 0 \leq DPI \leq 1/2
\end{array}\right.
\end{align*}
\]
\[
\sum_{i \in \mathbb{N}} \sum_{j \in \mathbb{N}} t_{ij} x_{ijk} \sim N \left( \sum_{i \in \mathbb{N}} \sum_{j \in \mathbb{N}} \left( \frac{c_{ij}}{w_{ijk}} + TL_j \right) x_{ijk} - B_k, \sum_{i \in \mathbb{N}} \sum_{j \in \mathbb{N}} \sigma_{ijk}^2 x_{ijk} \right)
\]

(19)

We can rewrite this formulation into the following one.

\[
P \left( \eta \leq \frac{\sum_{i \in \mathbb{N}} \sum_{j \in \mathbb{N}} \left( \frac{c_{ij}}{w_{ijk}} + TL_j \right) x_{ijk} - B_k}{\sqrt{\sum_{i \in \mathbb{N}} \sum_{j \in \mathbb{N}} \sigma_{ijk}^2 x_{ijk}}} \right) \geq \alpha
\]

(20)

4. Memetic algorithm

The problem considered in this study is a combination of facility relocation problem and vehicle routing problem. Therefore, the issue is more complicated, and it is an NP-hard problem. Exact methods, such as branch and price, cannot obtain the optimal solution in an acceptable time, especially for massive case problems. Therefore, we consider the meta-heuristic algorithm to solve our problem. MA is one of the most efficient population-based algorithm since it combines both intensification and diversification strategy, which has been used to solve many combinatorial problems [44]. In this study, the main idea of the memetic algorithm is the hybridization of a genetic algorithm with a local search operator.

4.1. Population initialization

As an individual is a solution, a population in an arbitrary generation is a set of solutions. Maintaining the diversity of the population is a very significant criterion to the convergence of MA. In this study, to avoid the premature convergence of MA, two different population initialization algorithms, including greedy algorithms and random algorithms are proposed. If the entire population is initialized by the same greedy algorithm, it will lead to the population containing similar solutions and very low diversity.

The initial solution is generated by three steps, which are shown in
Firstly, a random seed is selected, and then inserted to the current route by selecting the nearest GGS. Once the newly inserted GGS (for example, \(i\)) exceeds the capacity of the current route, \(i\) will be used as a new seed to construct a new route. The insertion will be continuously performed until all the GGSs are inserted into the route. Each route can be thought of as a cluster.

Secondly, for each route, the arithmetic mean of the route center (also called the class center) is obtained by calculating the arithmetic mean of the coordinates.

Finally, the open warehouse is allocated according to the distance between the center of the route and the distance between the STPs and the capacity of the STPs. Specifically, this step can be divided into two strategies.

Strategy (1), randomly select a route as a seed, pick the nearest STP, then assign the closest routes to the STP until the STP capacity is exceeded. The strategy uses the route as the seed to choose to open the nearest STP and then allocates the adjacent route to the STP in turn until all the routes are allocated.

Strategy (2) tends to open STPs with large capacity and then allocates routes according to the nearest neighbor principle. This strategy will allow reducing the number of open STPs.

### 4.2. Chromosome design

The proper representation for a chromosome which should satisfy three principles: non-redundancy, soundness and completeness, plays a significant role in the development of MA. In this study, inspired from the work of Zhao et al. [45], a solution includes three parts: (1) opened STPs; (2) vehicles assigned to each opened STP and (3) the route information for each vehicle. Hence, we divide the chromosome into three segments and the chromosome design shows in Fig. 3. Now suppose that there are \(m\) gas gathering stations, an opened sewage treatment plant and \(n\) candidate STPs to construct sewage treatment plant, respectively. Assume that we now have \(k\) homogeneous vehicles. In Fig. 3, the first segment represents the GGS information and each bit corresponds to a GGS. The value in each bit of the first segment represents a specified vehicle serviced to the gas gathering station.

The second segment represents the information of GGSs. The last segment represents the information of vehicles assigned to STPs. The value in each bit in the last segment represents the STP that the vehicle serviced. Considering the particularity of the model in this study: that point \(O\) must be selected, and at least one vehicle and one GGS are served by the STP. In this paper, we design a reasonable chromosome structure.

In order to describe the decoding process in more detail [45], a specific and small size example is given, assuming that \(m = 15\), \(n = 3\), and \(k = 4\), which is shown in Fig. 4.

Fig. 5 shows the GGSs serviced by each vehicle, which can be derived from the segment 1 of Fig. 4.

By using the information from Fig. 5, we can derive the values of indexes shown in segment 2 of Fig. 4. Finally, we can obtain the routes of each vehicle by using the genes and index information in segment 2. The final vehicle routes are shown in Fig. 6.

In this study, the solution is represented with a list that contains the information about routes and STPs. Encoding is the process of converting a solution into a chromosome. The main procedures of the encoding process are shown in Algorithm 1.

As an inverse process, decoding is the process of converting a chromosome into a solution. The pseudo of decoding is shown in Algorithm 2.

### 4.3. Fitness evaluation

The goal of this study is to minimize the total costs. Hence, the fitness function takes the reciprocal of the objective function. When the
4.4. Main operators

Selection In this study, we mainly consider the elite retention strategy and the roulette method, which are also adopted by Podlena and Hendtlass [46]. First, the elite retention strategy is applied, the individuals with the highest fitness do not participate in the cross mutation and directly pass to the next generation. Then the remainder of the populations will be applied parents selection operation by using the roulette wheel method.

Crossover Crossover operation is a significant operation in MA to generate new gene information. Due to the special structure of chromosome which shows in Fig. 3, we apply different crossover operation methods for each segment of the chromosome. The encoding method of segment 1 and segment 3 are similar; hence they can apply the same crossover operation. The two-point intersections and the partially mapped crossover are adopted for segment 1, 3 and segment 2, respectively [47].

The two-point intersection is widespread and popular crossover operation used in the evolutionary algorithms. Here we omit the explanations of the two-point intersection. Detailed information about two-point intersection can be found in Fu [48].

The partially mapped crossover consists of four steps including substring selection, sub-string exchange, mapping list determination and offspring legalization. Here we give an example to illustrate the four steps of partially mapped crossover operation. Fig. 7(a) shows the chromosomes of two parents. First two sub-strings are randomly selected (Fig. 7(b)). Then, the two sub-strings are exchanged (Fig. 7(c)). According to the mapping relationship between the gene of two offspring, two mapping lists are determined as shown in Fig. 7(d). Finally, the two offspring are legalized with the mapping relationship (Fig. 7(e)).

Mutation Mutation strategy plays a significant role in enhancing the global searching ability and getting rid of local optimal. In this study, two different mutation operation strategies, including swap mutation and reverse mutation, are adopted for segment 1, 3, and segment 2 of the chromosome, respectively. In swap mutation, first, two positions on segments 1 and segment 3 are random selected (Fig. 8(b)). The values on segment 2 of the chromosome are randomly selected, respectively. Then the values on segment 1 and segment 3 are interchanged. Fig. 8 shows an example of a reverse mutation in segment 2 of the chromosome, which helps us understand how we can generate an offspring. First, we select genes randomly in the parent. The randomly selected subset genes is shown in Fig. 8(a). Then we invert the entire genes in the subset, and the offspring is shown in Fig. 8(b).

Local search As discussed by Decerle et al. [49], the local search strategies could be regarded as a learning stage for improving an individual. The local search operator aims to find a local optimal solution on the basis of the current individual, and it plays an essential role in improving individuals and boosting convergence in MA. In this section, considering the structure of the solution, we have designed six operators, which have comprehensive considerations in the searching space.

Table 3
Parameters for our model and experiments.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mathematical Model</td>
<td>$w$: the average price for each unit distance $(i,j)$</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>$v_{ij}$: the average traveling speed during arc $(i,j)$</td>
<td>30 unit/min</td>
</tr>
<tr>
<td></td>
<td>$b_k$: the due time for each vehicle $k$</td>
<td>480 min</td>
</tr>
<tr>
<td></td>
<td>$T_{Lk}$: the loading time in GGS $k$</td>
<td>30 min</td>
</tr>
<tr>
<td></td>
<td>$d_{ijk}$: the fuzzy AGS of GGS $i$ (represented by the nominal AGS $d_i$)</td>
<td>$[0.8d_i, d_i, 1.2d_i]$</td>
</tr>
<tr>
<td></td>
<td>$\alpha$: the confidential value in stochastic travel time constraint</td>
<td>0.8</td>
</tr>
<tr>
<td></td>
<td>$\sigma$: the standard deviation of travel time between arc $i,j$ in vehicle $k$</td>
<td>$0.2 + t_{lk}$</td>
</tr>
<tr>
<td>Memetic Algorithm</td>
<td>popsize: the number of individuals in the population.</td>
<td>50</td>
</tr>
<tr>
<td></td>
<td>maxgen: the max iteration of the MA.</td>
<td>$50 \times$ size of the instance.</td>
</tr>
<tr>
<td></td>
<td>rand_ratio: the percentage of the randomly generated individuals in the initial population.</td>
<td>90%</td>
</tr>
<tr>
<td></td>
<td>pc: the percentage of elite in the current population taht will be kept in the offspring.</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>pc: the percentage of individuals selected to take part in crossover.</td>
<td>0.8</td>
</tr>
<tr>
<td></td>
<td>pm: the percentage of individuals selected to take part in mutation.</td>
<td>0.07</td>
</tr>
<tr>
<td></td>
<td>pl: the percentage of individuals selected to take part in local search.</td>
<td>1</td>
</tr>
<tr>
<td>stochastic Simulation</td>
<td>M: the times for stochastic simulation</td>
<td>500</td>
</tr>
<tr>
<td>instance ID</td>
<td>LB</td>
<td>GRASP</td>
</tr>
<tr>
<td>-------------</td>
<td>------------</td>
<td>-------------</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cost</td>
</tr>
<tr>
<td></td>
<td>nb_depot</td>
<td>nb_vehicle</td>
</tr>
<tr>
<td></td>
<td>cd</td>
<td>cr</td>
</tr>
<tr>
<td></td>
<td>gap1 (MA VS LB)</td>
<td>gap2 (MA VS GRASP)</td>
</tr>
<tr>
<td>20-5-1a</td>
<td>54,793</td>
<td>55,131</td>
</tr>
<tr>
<td>20-5-1b</td>
<td>39,104</td>
<td>39,104</td>
</tr>
<tr>
<td>20-5-2a</td>
<td>48,908</td>
<td>48,908</td>
</tr>
<tr>
<td>20-5-2b</td>
<td>37,542</td>
<td>37,542</td>
</tr>
<tr>
<td>50-5-1</td>
<td>87,109.64</td>
<td>90,160</td>
</tr>
<tr>
<td>50-5-1b</td>
<td>63,256</td>
<td>63,256</td>
</tr>
<tr>
<td>50-5-2</td>
<td>86,055.01</td>
<td>88,715</td>
</tr>
<tr>
<td>50-5-2b</td>
<td>67,698</td>
<td>67,698</td>
</tr>
<tr>
<td>50-5-2bis</td>
<td>84,439</td>
<td>84,439</td>
</tr>
<tr>
<td>50-5-2bbis</td>
<td>51,822</td>
<td>51,822</td>
</tr>
<tr>
<td>50-5-3</td>
<td>272,062.37</td>
<td>277,935</td>
</tr>
<tr>
<td>50-5-3b</td>
<td>186,916.59</td>
<td>198,113</td>
</tr>
<tr>
<td>100-5-1</td>
<td>258,242.64</td>
<td>291,887</td>
</tr>
<tr>
<td>100-5-1b</td>
<td>218,825.96</td>
<td>235,532</td>
</tr>
<tr>
<td>100-5-2</td>
<td>226,904.99</td>
<td>246,708</td>
</tr>
<tr>
<td>100-5-2b</td>
<td>158,270.05</td>
<td>157,792</td>
</tr>
<tr>
<td>100-5-3</td>
<td>194,202.03</td>
<td>201,952</td>
</tr>
<tr>
<td>100-5-3b</td>
<td>149,985.58</td>
<td>154,709</td>
</tr>
<tr>
<td>100-10-1</td>
<td>258,242.64</td>
<td>291,887</td>
</tr>
<tr>
<td>100-10-1b</td>
<td>218,825.96</td>
<td>235,532</td>
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<td>226,904.99</td>
<td>246,708</td>
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<td>100-10-2b</td>
<td>158,270.05</td>
<td>157,792</td>
</tr>
<tr>
<td>100-10-3</td>
<td>194,202.03</td>
<td>201,952</td>
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<tr>
<td>100-10-3b</td>
<td>149,985.58</td>
<td>154,709</td>
</tr>
<tr>
<td>200-10-1</td>
<td>–</td>
<td>–</td>
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<td>–</td>
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<tr>
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<tr>
<td>200-10-2b</td>
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<td>–</td>
</tr>
<tr>
<td>200-10-3</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>200-10-3b</td>
<td>–</td>
<td>–</td>
</tr>
</tbody>
</table>

Note: nb_vehicle: number of vehicles; nb_depot: number of depots; cd: cost of depots; cr: cost of routes.
The introduction of the operators is described as follows, and they are depicted in Fig. 9.

(op1) intra-route-swap: two GGSs are randomly selected, and their positions are swapped.

(op2) intra-route-reverse: two GGSs are randomly selected, then all the arcs along the two vertices are reversed.

(op3) inter-route-opt: two GGSs in different routes are selected, then their places are swapped.

(op4) inter-route-insert: a GGS, and also a route excluding this GGS are randomly selected, then the GGS is inserted to the best position of the selected route.

(op5) inter-STP-opt: two STPs are randomly chosen, then the two STPs are swapped.

(op6) inter-STP-insert: one STP is selected, and another un-enabled STP replaces the current STP.

Generally, the six operators could be divided into three categories, namely (op1) and (op2) can be viewed as the improvement of a single route, while (op3) and (op4) are regarded to optimize the assignment of GGSs and vehicles. Finally, (op5) and (op6) are performed at the location stage. What should be highlighted here is that, in the local search, (op4) can help reduce the number of used vehicles and reduce the number of opened STPs.

As presented above, each operator has a different role in exploring the solution space and finding a new solution. Considering that performing all the operators for a single individual in one generation may be time-consuming, we choose to perform one operator in one generation each time. All the operators are selected randomly but with the same probability and the pseudo is shown in Algorithm 4. We find that the complexity of the local search algorithm is $O(n^2)$.

4.5. Framework of the proposed MA

We summarize the conceptual framework of the proposed MA as follows.

Step (1): Initialize the population with three greedy methods and random method, then evaluate all the individuals.

Step (2): Move the elitist individuals to the next generation.

Step (3): Apply parents selection and crossover operation to generate new offsprings.

Step (4): Do mutation operation for all the individuals with the mutation probability.

![Fig. 11. The costs change tendencies with different DPI values.](image)

**Fig. 11.** The costs change tendencies with different DPI values.

![Fig. 12. Evaluating procedures of each solution in an uncertain environment.](image)

**Fig. 12.** Evaluating procedures of each solution in an uncertain environment.

<table>
<thead>
<tr>
<th>Instance ID</th>
<th>DPI</th>
<th>TC</th>
<th>AC</th>
<th>nb_depot</th>
<th>nb_vehicle</th>
<th>cd</th>
<th>cr(PC)</th>
<th>Total routes</th>
<th>computing time (s)</th>
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<td>4</td>
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<td>31,999</td>
<td>45,281</td>
<td>58,616.96</td>
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<td></td>
<td>0.1</td>
<td>89324.64</td>
<td>3</td>
<td>5</td>
<td>25,908</td>
<td>56,836</td>
<td>63,934.90</td>
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<td>81639.52</td>
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<td>55,967.12</td>
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<td>0</td>
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<td>55,607</td>
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<td>667,707</td>
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<td>1.0</td>
<td>79,497</td>
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<td>53,589</td>
<td>53,589.00</td>
<td>766,437</td>
<td></td>
</tr>
</tbody>
</table>

Note: nb_vehicle: number of vehicles; nb_depot: number of depots (STPs); cd: cost of depots (STPs); cr: cost of routes; TC: total cost; AC: additional cost; PC: planned cost.
Table 6: Comparison between deterministic AGS and fuzzy AGS models.

<table>
<thead>
<tr>
<th>Instance</th>
<th>Deterministic demand model</th>
<th>Fuzzy demand model</th>
</tr>
</thead>
<tbody>
<tr>
<td>URLRP20-5-1</td>
<td>TC: 74,897.03, AC: 329.8, nb_depot: 3, nb_vehicle: 25,908, cd: 48,989, cr: 83,107, ct: 0.00</td>
<td>TC: 25,908, AC: 36,953, nb_depot: 3, nb_vehicle: 25,908, cd: 48,989, cr: 83,107, ct: 0.00</td>
</tr>
<tr>
<td>URLRP20-5-1b</td>
<td>TC: 57,771.00, AC: 0.00, nb_depot: 2, nb_vehicle: 25,076, cd: 32,695, cr: 60,742, ct: 0.00</td>
<td>TC: 25,076, AC: 35,666, nb_depot: 2, nb_vehicle: 25,076, cd: 32,695, cr: 60,742, ct: 0.00</td>
</tr>
<tr>
<td>URLRP20-5-2b</td>
<td>TC: 49,361.01, AC: 116.7, nb_depot: 2, nb_vehicle: 21,619, cd: 27,742, cr: 57,661, ct: 0.00</td>
<td>TC: 21,619, AC: 36,042, nb_depot: 2, nb_vehicle: 21,619, cd: 27,742, cr: 57,661, ct: 0.00</td>
</tr>
<tr>
<td>URLRP50-5-1</td>
<td>TC: 153,009.02, AC: 1985, nb_depot: 2, nb_vehicle: 20,100, cd: 132,909, cr: 158,849, ct: 0.00</td>
<td>TC: 20,100, AC: 138,749, nb_depot: 2, nb_vehicle: 20,100, cd: 132,909, cr: 158,849, ct: 0.00</td>
</tr>
<tr>
<td>URLRP50-5-1b</td>
<td>TC: 105,635.04, AC: 391.96, nb_depot: 2, nb_vehicle: 20,100, cd: 85,535, cr: 112,562, ct: 0.00</td>
<td>TC: 20,100, AC: 92,462, nb_depot: 2, nb_vehicle: 20,100, cd: 85,535, cr: 112,562, ct: 0.00</td>
</tr>
<tr>
<td>URLRP50-5-2</td>
<td>TC: 154,914.07, AC: 697.8, nb_depot: 3, nb_vehicle: 36,094, cd: 118,820, cr: 164,890, ct: 0.00</td>
<td>TC: 36,094, AC: 128,597, nb_depot: 3, nb_vehicle: 36,094, cd: 118,820, cr: 164,890, ct: 0.00</td>
</tr>
<tr>
<td>URLRP50-5-2BIS</td>
<td>TC: 145,178.02, AC: 1757.72, nb_depot: 3, nb_vehicle: 19,816, cd: 125,362, cr: 163,040, ct: 0.00</td>
<td>TC: 19,816, AC: 143,224, nb_depot: 3, nb_vehicle: 19,816, cd: 125,362, cr: 163,040, ct: 0.00</td>
</tr>
<tr>
<td>URLRP50-5-2b</td>
<td>TC: 114,571.00, AC: 0.00, nb_depot: 3, nb_vehicle: 36,094, cd: 78,477, cr: 130,433, ct: 0.00</td>
<td>TC: 36,094, AC: 94,339, nb_depot: 3, nb_vehicle: 36,094, cd: 78,477, cr: 130,433, ct: 0.00</td>
</tr>
<tr>
<td>URLRP50-5-2bBIS</td>
<td>TC: 92,944.08, AC: 754.9, nb_depot: 3, nb_vehicle: 19,242, cd: 73,702, cr: 95,440, ct: 0.00</td>
<td>TC: 19,242, AC: 76,198, nb_depot: 3, nb_vehicle: 19,242, cd: 73,702, cr: 95,440, ct: 0.00</td>
</tr>
<tr>
<td>URLRP50-5-3</td>
<td>TC: 134,526.01, AC: 1250.5, nb_depot: 2, nb_vehicle: 24,173, cd: 110,353, cr: 144,400, ct: 0.00</td>
<td>TC: 24,173, AC: 111,868, nb_depot: 2, nb_vehicle: 24,173, cd: 110,353, cr: 144,400, ct: 0.00</td>
</tr>
<tr>
<td>URLRP50-5-3b</td>
<td>TC: 105,989.02, AC: 17, nb_depot: 3, nb_vehicle: 24,173, cd: 81,816, cr: 111,257, ct: 0.00</td>
<td>TC: 24,173, AC: 87,064, nb_depot: 3, nb_vehicle: 24,173, cd: 81,816, cr: 111,257, ct: 0.00</td>
</tr>
</tbody>
</table>

Note: nb_vehicle: number of vehicles; nb_depot: number of depots (STPs); cd: cost of depots (STPs); cr: cost of routes; TC: total cost; AC: additional cost; PC: planned cost.

Fig. 10 shows the conceptual framework of the proposed MA.

5. Experimental results

In the above sections, we have formulated a model named RLRPFSSSTT and proposed a memetic algorithm based heuristic to solve the problem. This section mainly reports and analyzes some of the experimental results. As mentioned, the RLRPFSSSTT is not only a feature of combinatorial optimization, but also belongs to uncertain optimization. So, the classical commercial solvers like CPLEX, or Gurobi could not solve the model directly.

To validate the proposed models and algorithms, we have performed several series of experiments. In this section, firstly, the newly developed instances are presented in Section 5.1, then Section 5.2 reports the experimental results for the reduced model. Thirdly, the detailed experiments and analysis of the uncertain model are presented in Section 6.3, in which the sensitivity analysis of parameters are also performed to guide the policymakers.

5.1. Introduction to the instances

To the best of our knowledge, no standard benchmark instances in the literature are completely suitable for our problem. We generate instances for our problem based on the benchmark instances provided by Prins et al. [9]. The instances generated by Prins et al. [9] are grouped into a few groups according to their scale of customers and depots. Each category has its own characteristic of depots and customers. For each instance, Prins et al. [9] has defined coordinates of the location, demand, the value of capacity, and fixed cost.

In our studied problem, there is an analogy with the instances developed by Prins et al. [9]. Each STP corresponds to one depot, and every GGS is equivalent to a customer. We make no changes to the customers’ locations, AGS, and capacity in Prins et al. [9]’s original instances, but we have introduced the following changes to the original data to adapt it to our problem. Firstly, we assume that the first GGS is the original built, and others are new location candidates waiting to be selected. Secondly, we consider a uniform speed between arcs. Thirdly, we have added a new parameter DPI to make the trade-off between the risk and full utilization of the vehicles and STPs. To distinguish the difference between our instances and classical instances of Prins et al. [9], we name our instances as “URLRP-a-b-X,” in which a is the number of GGS, while b is the number of STP, and X is the specific name of this instance. All the codes are implemented by java in the ubuntu 18.04 system on the laptop with Intel®Core™ i7 Processors and 2.4 GHZ.

The main parameters used in the proposed algorithms and model are listed in Table 3. The tuning of the parameters are obtained by the Design of Experiments [50].

5.2. Comparison with the published results

Because the proposed model is entirely new, and no other researcher has solved these same instances, we could not compare the published works to validate our proposed heuristics. Our problem will be reduced to a classical LRP presented by Prins et al. [9] if we assume the following aspects. (1) The constraints of the fuzzy AGS and stochastic travel times become deterministic. (2) The original set if STP is an empty set; STPs and GGSs are regarded as depots and customers, respectively. To validate the efficiency of our algorithm, we first apply the MA to test the instance of Prins et al. [9].

Table 4 reports the results of MA and GRASP for solving the classical benchmarks. The first column shows the ID of the instance by indicating

Step (5): Apply local search to the newly generated offsprings.
Step (6): Calculate the fitness value for all the individuals.
Step (7): If the stop conditions are met, return the best solution otherwise go to Step (2).

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Fig. 10 shows the conceptual framework of the proposed MA.
the size. For example, 20-5-1 discloses that the number of customers is 20, and the amount of given candidates for building depots is 5. The BKs column indicates the best solutions found so far. The LB column has missing values because it is difficult to seek a good lower bound in a limited time when the instances’ size becomes greater. We report our results in the final column with MA by comparing them with BKs and Prins et al. [9]. As shown in the last column, we find that for nine instances, the GRASP approach gives better solutions; for two instances, we have the same solutions, and for the remaining instances, our approach is better. We have also made a full comparison with the recent results reported by Lopes et al. [51] and Peng et al. [52]. Please check the detail in the supplementary material.

We would like to emphasize that this article’s primary purpose is not to develop the best algorithm to obtain a better algorithm than historical results. Instead, this article summarized a model from a practical problem, and the most exciting part is to develop an effective heuristic algorithm to solve the real-life application. The comparison with the published results is only used to illustrate the proposed MA is effective and acceptable. The proposed MA will be applied to solve the uncertain optimization problem in the next section.

5.3. Results of the uncertain optimization results

5.3.1. Sensitivity analysis

As mentioned before, DPI is an essential parameter for helping decision-makers make a reasonable decision. However, the value of DPI is unknown in advance, and it is selected by empirical experiments, which can be regarded as sensitivity analysis of DPI value. As an example, we have chosen an instance named URLRP20-5-1. In this part, let the value of DPI vary within the interval [0, 1] with a step of 0.1, then record the simulation results of the best solutions.

The simulation results for URLRP20-5-1 can be found in Table 5 and Fig. 11. These tables and figures show tendencies regarding the cost caused by the planned distances (PC), additional cost caused by the additional distances due to failures (AC), the cost for total distance (TC), and other indicators that vehicles covered as the dispatcher preference index varies. We observe that with the increase of the DPI value, the AC decreases, and there is no clear trend in the TC and PC. For instance URLRP20-5-1, the AC strictly decreases as DPI value increases from 0 to 0.6. However, when DPI ∈ [0.7, 1], the AC becomes 0, and this means that there is no failure route. According to these results, we find that 0.8 is the best DPI value to make the decision.

As mentioned in Section 4.2, DPI expresses the dispatcher’s attitude toward risk. When the dispatcher is not risk-averse, he/she will choose lower values of parameter DPI. This scenario indicates that the dispatcher does not prefer risk-averse. When DPI is with a high value, the dispatcher prefers risk-averse, which would decrease the chance of generating additional cost due to the failure routes. The simulation results in Table 5 empirically prove this point.

5.3.2. Comparison with deterministic AGS model

As we have discussed, when the DPI value is low, the decision-maker subjectively desires to make full use of the vehicle, so the PC is minimal. In this situation, the chance that the vehicles may not meet the GGSs’ AGS increases, and the driver has to return to the STP to load more AGS. These failure routes bring more additional distances, leading to the delay of the service time. Higher values of DPI are characterized by lower vehicle capacity utilization along the planned routes and less AC due to fewer failures.

To further compare with the deterministic AGS model, we have performed a Monte Carlo Simulation for each solution by assuming it under an uncertain environment. The procedures can be described by Fig. 12, and a detailed algorithm is given in Algorithm 3. Table 6 summarizes the comparison results.

Table 6 reports the simulation results of the solutions obtained by considering the fuzzy AGS and deterministic AGS model. We set the parameter DPI as 0.8, which is the best DPI value. In these scenarios, AC is equal to 0, which means there is no failure route. However, the solutions obtained by deterministic AGS show a high AC, which discloses that, in this situation, these solutions tend to have more failure routes. Finally, when comparing the TC, the solution with considering fuzzy AGS is slightly more expensive than without considering fuzzy information. The t-test is to use the t distribution theory to infer the probability of the difference, so as to compare whether the difference between two averages is significant. We carried out a t-test on the values of TC in the group named “deterministic model” and group called “fuzzy model”. We find that the t-value equals to 0.2455 (greater than 0.05, reject the hypothesis), which indicates that the values of TC has no significant different.

Considering that robustness is one of the most critical issues in gas production, it is still acceptable to pay a slight additional cost. So, we may conclude that the relocation-routing model considering fuzzy AGS is more reasonable to help the policy-makers make reasonable decisions about relocation and vehicle routing problem.

6. Conclusions

Most of the previous studies found in the literature about gas-field logistics systems tend to study the location problem of the facility separately from the vehicle routing problem. Some gas production enterprises failed to predict their production in the early enough, and when the facility (such as STP) could not satisfy high scale of production, the policymakers intend to build some new facilities. The objective of this issue is to minimize the total cost, including fixed cost of the newly built facilities, logistics costs. This article, considering this scenario, proposed a fuzzy chance-constraint for a relocation-routing problem in the area of green production of gas. Fuzzy AGS and stochastic travel time were taking into account in this model. Given that the model has attributes of combinatorial optimization and uncertain programming, we developed a solving approach by integrating MA and Monte Carlo simulation.

To validate the proposed approach, first, the model was reduced to the classical LRP. Then the comparison with Prins et al. [9] and Prins et al. [10] shows that MA is an effective and efficient algorithm for this study. Then MA was applied to solve the fuzzy chance constraints. The AC due to route failures was estimated by Monte Carlo simulation procedures for each planned route. Several different sizes of test instances are then generated, and the computational experiments showed that the dispatcher preference index greatly influenced the planned cost, additional cost, and total cost. Best DPI were obtained from empirically analysis by changing the DPI value with a step of 0.1 gradually. Finally, the comparison between the solutions obtained by the fuzzy AGS model and the deterministic AGS model validates the strength of considering fuzzy AGS. The best DPI obtained by our model and algorithm can help the decision-makers make a better decision when they trade off the cost and risk.

The location-routing problem is a subject that has been widely studied in the manufacturing industries. But the current related research is aimed at helping companies plan a completely new logistics layout. In developing countries, many companies are facing business expansion. This means that the most primitive logistics layout cannot meet the growing development needs. Therefore, it is necessary to optimize further and add new logistics facilities on the basis of the original logistics facility layout to keep the entire logistics system in an optimal state. Therefore, this research is an essential reference value for making up for the existing deficiencies and providing logistics decision-making for developing enterprises.

The limitation of this paper is that the model does not consider the dynamic changes [53] of AGS and carbon emission of the vehicles [54], which could be the main work of future research. On the other side, some senior techniques will also be nested into meta-heuristic to improve the efficiency of this solving approach.
Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.sweco.2022.101129

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